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ORIGINAL PAPER

Modeling compatible single-tree aboveground biomass equations for masson pine (*Pinus massoniana*) in southern China

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Abstract: Because of global climate change, it is necessary to add forest biomass estimation to national forest resource monitoring. The biomass equations developed for forest biomass estimation should be compatible with volume equations. Based on the tree volume and aboveground biomass data of Masson pine (*Pinus massoniana* Lamb.) in southern China, we constructed one-, two- and three-variable aboveground biomass equations and biomass conversion functions compatible with tree volume equations by using error-in-variable simultaneous equations. The prediction precision of aboveground biomass estimates from one variable equation exceeded 95%. The regressions of aboveground biomass equations were improved slightly when tree height and crown width were used together with diameter on breast height, although the contributions to regressions were statistically insignificant. For the biomass conversion function on one variable, the conversion factor decreased with increasing diameter, but for the conversion function on two variables, the conversion factor increased with increasing diameter but decreased with increasing tree height.

Keywords: aboveground biomass; error-in-variable simultaneous equations; mean prediction error; compatibility; *Pinus massoniana*

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Introduction

Since forest ecosystems play irreplaceable roles in regulating the global carbon balance and mitigating global climate change, forest biomass monitoring is becoming important all over the world. It is necessary to develop generalized single-tree biomass models for large scale forest biomass estimation to enhance monitoring and assessment of national forest biomass. Stem biomass, which is equal to stem volume multiplied by wood density, contributes about 70% of total aboveground biomass of an individual tree. Thus, aboveground biomass is closely related to tree volume. National monitoring of forest volume estimated by tree volume equations has been conducted for several decades, but national monitoring of forest biomass estimated by tree biomass equations has only been implemented during recent years in some countries but not in many countries including China (Tomppo et al. 2010). Considering the close relationship between biomass and volume, biomass equations should be compatible with volume equations when forest biomass is added to national forest resource monitoring.

The compatibility or additivity between total biomass and biomass components was studied by several researchers (Parresol 1999 and 2001; Bi et al. 2004). Hansen (2002) compared and analyzed the consistency and accuracy of volume and biomass estimates in the Forest Inventory and Analysis (FIA) program of the USDA Forest Service. He concluded that the use of various data sources for modeling and different model forms resulted in inconsistency in estimates for trees of the same species and sizes but at different locations. He did not discuss the compatibility between biomass and volume equations. Studies of compatibility have been largely confined to those between total biomass and biomass components in China (Zhang et al. 1999; Xu and Liu 2001; Xing and Wang 2007; Cheng et al. 2007 and 2008). Only a few studies addressed compatibility with volume while considering the additivity between total biomass and biomass component equations (Xu 1999b; Luo et al 1999; Zeng et al. 1999a; Tang et al 2000). Tree volume was simply regarded as an ex-

plainable variable, like diameter and height, of the biomass equation, and the compatible volume equation was not simultaneously established. Thus, the following problems resulted: (1) volume estimated from diameter and height, but not measured directly by field survey, is an error-in-variable, not an error-free-variable, so the volume was regarded as an explainable variable without error in the biomass equation; (2) error was introduced when the biomass equation was applied to estimate forest biomass, because the volume was estimated from other volume equation, not from a compatible one; (3) the parameter estimates may be unstable because of the self-correlation among diameter, height and volume.

Aiming at solving above problems, the error-in-variable simultaneous equations (Tang et al 2001; Tang and Wang 2002; Tang and Li 2002; Tang et al 2008) were used in our study. Based on the tree volume and aboveground biomass data of Masson pine (*Pinus Massoniana* Lamb.) in south China, we first constructed one-, two- and three-variable aboveground biomass equations and biomass conversion functions compatible with tree volume equations. We then compared the series of aboveground biomass equations with each other, and analyzed the properties of biomass conversion functions with increasing diameter and height.

Materials and methods

Data from 150 sample trees in our study consisted of aboveground biomass and tree volume measurements of Masson pine in south China that were derived from destructive sampling in 2009. The sample trees were located in Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Hunan, Guangdong, and Guizhou Provinces and Guangxi autonomous region in China (about 20°–35° N, 102°−123° E). The sample trees were approximately distributed according to the proportion to stocking volume of Masson pine forests in these nine provinces or autonomous regions. The sample trees were distributed evenly in 10 diameter classes of 2, 4, 6, 8, 12, 16, 20, 26, 32, and more than 38 cm. The trees in each diameter class were distributed by 3–5 height classes as evenly as possible. Thus, the samples were representative of forests in the large-scale region. Diameter at breast height and crown width of sample trees were measured in the field. After the tree was felled, the total length (tree height) and length of live crown were measured. The trunk was divided into 11 sections at points corresponding to 0, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 of tree height. Base diameters of all sections were measured, and the tree volume was computed using Smalian's formula. In addition, the fresh weights of stem wood, stem bark, branches and foliage were measured, and the subsamples were selected and weighed in the field. After removal to the laboratory, each subsample was oven dried at 85°C until a constant weight was reached. According to the ratio of dry weight to fresh weight, each compartment biomass was computed and the aboveground biomass of the tree was obtained by summation. Data are summarized in Table 1.

Table 1. The general data of sample trees

Statistics	Diameter (cm)	Height (m)	Crown width (m)	Crown length (m)	Tree volume (1/1000 m^3)	Aboveground biomass (kg)
Mean	16.6	12	4.47	6.24	301.59	169.1
Min	1.5	2	0.6	1.3	1.22	0.317
Max	47.2	27.6	12	17.52	1825.45	1039.144
S.D.	12.1	7.2	2.55	3.56	175.36	233.739

Modeling compatible equations

Error-in-variable model

For commonly used regression models, it is assumed that observed values of independent variables exclude errors, and observed values of dependent variables include errors. The errors may result from various sources, such as sampling error and observing error, which are generally called measurement error. When observed values of both independent and dependent variables include measurement error, the ordinary least squares (OLS) method is no longer adequate, and two-stage error-in-variable modeling method is necessary for fitting the regression model (Tang et al 2001; Tang and Wang 2002; Tang and Li 2002). Li et al. (2004) established compatible growth table and volume table using the error-in-variable modeling method; Li and Tang (2006) studied the estimation procedure of the whole stand model with measurement error, and concluded that the simultaneous nonlinear error-in-variable equations method was better than the OLS method.

Multivariate nonlinear error-in-variable simultaneous equations (also called nonlinear error-in-variable model) are of the following vector form (Tang et al. 2008):

$$\begin{cases} f(y_i, x_i, c) = 0 \\ Y_i = y_i + e_i, i = 1,2,\cdots,n \\ E(e_i) = 0, \operatorname{cov}(e_i) = \sigma^2\psi \end{cases} \tag{1}$$

where, x_i is the observed value of q-dimensional error-free-variable, y_i the observed value of p-dimensional error-in-variable, $f()$ the m-dimensional vector function, and Y_i is the unknown true value of y_i. The covariance matrix of error e_i is denoted as $\phi = \sigma^2\psi$, where ψ is the structure matrix of error e_i, and σ^2 is the error of the estimate.

Compatible models

According to the ministerial standard LY208-77 in China, the standard form for the two-variable tree volume equation is as follows (Ministry of Agriculture and Forestry 1978):

$$V = a_0 D^{a1} H^{a2} \tag{2}$$

where, V is the tree volume (m^3), D is the diameter at breast height (1.3 m) (m), H the tree height (m), and a_0, a_1, a_2 are parameters.

The nonlinear tree biomass equation was commonly expressed as (Parresol 1999 and 2001):

$$M = b_0 x_1^{b1} x_2^{b2} \cdots x_i^{bi} \tag{3}$$

where, M is the aboveground biomass of a single tree, x_i is a tree size variable such as D or H, and b_i is the model parameter. If only two variables are considered for the biomass equation, then model (3) takes the same form:

$$M = b_0 D^{b1} H^{b2} \tag{4}$$

Considering the close relationship between biomass and volume, and according to previous results (Xu 1999a; Zeng et al. 1999a; Luo et al. 1999; Tang et al. 2000), the regression model on two variables between biomass and volume can be expressed as follows:

$$M = f(D,H) \cdot V = c_0 D^{c1} H^{c2} \cdot V \tag{5}$$

where, $f(D,H)$ is the conversion function from volume to biomass (also called conversion factor), and c_i is the model parameter. Obviously, from models (2), (4) and (5), the following relations can be obtained:

$$c_0 = \frac{b_0}{a_0}, c_1 = b_1 - a_1, c_2 = b_2 - a_2 \tag{6}$$

If models (2), (4) and (5) were estimated independently, the parameter estimates would not meet the needs of expression (6). Therefore, to insure compatibility between aboveground biomass M and tree volume V, we developed a system of nonlinear error-in-variable simultaneous equations based on models (2) and (5) where D and H were regarded as error-free-variables, and V and M as error-in-variables. The system parameters were estimated by using two-stage error-in-variable modeling, so that the volume and biomass equations based on the same data sets were compatible with each other, and a compatible conversion function from tree volume to aboveground biomass was also obtained. For comparison, the regression models on one variable D and three variables D, H and Cw (crown width) were fitted too, and they are simply called one-variable model and three-variable model, respectively. In addition, to make the conversion values from volume to biomass harmonious, we set the units of biomass M and volume V to be kg and 1/1000 m^3, respectively.

Processing of heteroscedasticity

Biomass and volume data exhibit heteroscedasticity (Luo et al. 1992; Zeng 1996 and 1998; Zeng et al. 1999b; Zhang et al. 1999; Xu 1999b; Parresol 1999 and 2001), that is, the error variances are not constant for all observations. If models (2) and (5) are fitted with such data, some countermeasures are necessary to eliminate heteroscedasticity. Logarithmic regression and weighted regression are commonly used methods (Zeng and Tang 2011). We used the latter for nonlinear models (2) and (5), and we determined the weight function of each model from the regression equation fitted independently by OLS. The fitting results of weighted regression, using general weight function ($W=1/f(x)^2$) presented by Zeng (1998) and the weight function based on residual errors of the model estimated independently by OLS were compared with each other. The two weights worked well and the latter function was slightly better. Then we compared the weight functions on one or two variables derived from residual errors of models fitted by OLS with similar results. Therefore, the weight functions were one variable regression equations, $e^2=g(D)^2$, deriving from residual errors of volume and biomass models fitted independently by OLS, and when ForStat2.1 (Tang et al. 2008) was used to estimate the parameters by the two-stage error-in-variable modeling method, two sides of the models (2) or (5) were multiplied by the weight factor $G=1/g(D)$.

Evaluation and test of models

We used three calculations for model evaluation, R^2 (determination coefficient), SEE (standard error of estimate), and MPE (mean prediction error). R^2, SEE and MPE are calculated by the following expressions (Parresol 1999; Zeng et al. 1999b):

$$R^2 = 1 - \sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2 \tag{7}$$

$$SEE = \sqrt{\sum (y_i - \hat{y}_i)^2 / (n-p)} \tag{8}$$

$$MPE = t_\alpha \cdot (SEE / \bar{y}) / \sqrt{n} \times 100 \tag{9}$$

where, y_i and $\hat{y}_i$ are the observed and estimated values of i-th sample tree, respectively, $\bar{y}$ the sample mean of observed values, n the number of sample trees, p the number of parameters, and t_α is the t-value for confidence level α with n-p degrees of freedom (for α=0.05, $t_\alpha \approx 1.98$).

Test of models

We applied three methods to test the models, hypothesis test of mean values for paired data, consistency test of regression models, and significance test of difference between models.

(1) Hypothesis test of mean values

Assuming that the difference between the mean values estimated from two biomass models was zero, that is, set H_0: μ_1-μ_2=0, and take the difference of paired estimates $d=x_1-x_2$ as a new variable. Then, the statistical index of t-value can be calculated as follows (Gao 2001):

$$t = \frac{\bar{d}}{S_{\bar{d}}} = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\dfrac{\sum (d - \bar{d})^2}{n(n-1)}}} = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\dfrac{\sum d^2 - n\bar{d}^2}{n(n-1)}}} \tag{10}$$

From the comparison between the t-value above and the critical t_a value with degree of freedom (n-1), we can determine whether the difference is significant or not between two biomass models. If t-value is larger than t_a, reject H_0, otherwise, accept it.

(2) Consistency test of regression models

Supposing that the estimates from two biomass models were y and x, respectively, and if the parameters (a, b) from the linear regression equation $y=a+bx$ were not significantly different from (0, 1), we concluded that the estimates of the two biomass models were consistent. The statistical index was calculated as follows (Tang et al. 2008):

$$F_A = \frac{\frac{1}{2}(a\sum y_i + b\sum x_i y_i - 2\sum x_i y_i + \sum x_i^2)}{\frac{1}{n-2}(\sum y_i^2 - a\sum y_i - b\sum x_i y_i)} \quad (11)$$

where, the F-distribution is with degrees of freedom f_1=2 and f_2=n-2. If $F_A>F_{0.05}$, then the two models were considered significantly different. In contrast, if $F_A \le F_{0.05}$, then the estimates of two models were not considered different.

(3) Significance test of difference between models

The difference between biomass models can be examined by use of the F-test. The F-statistic can be computed and compared with to a corresponding F-value to determine whether estimates are significantly different between two biomass models (Meng et al. 2008):

$$F_B = \frac{(SSE_1 - SSE_2)/(df_1 - df_2)}{SSE_2 / df_2} \quad (12)$$

where, SSE_1 and df_1 are the sum of the squared errors and degrees of freedom, respectively, of model (1). SSE_2 and df_2 are the sum of squared errors and degrees of freedom, respectively, of model (2).

Results

Compatible biomass equations

Using the tree volume and aboveground biomass data of 150 sample trees for Masson pine in south China, nonlinear error-in-variable simultaneous equations based on one, two and three variables were fitted through ForStat2.1, and the parameter estimates were used to compute the statistics from expressions (7)–(9). The parameter estimates and statistical indices of one-, two- and three-variable aboveground biomass equations and conversion functions compatible with tree volume are listed in Tables 2 and 3.

Table 2 Parameter estimates of compatible tree volume and aboveground biomass equations

Models	Parameter estimates										
	Volume equations			Biomass equations				Conversion functions			
	a_0	a_1	a_2	b_0	b_1	b_2	b_3	c_0	c_1	c_2	c_3
One-variable	0.14575	2.46775	/	0.10991	2.37379	/	/	0.75411	-0.09376	/	/
Two-variable	0.085755	1.89740	0.83854	0.078596	2.12525	0.40965	/	0.91652	0.22785	-0.42889	/
Three-variable	0.085419	1.89691	0.84055	0.078495	2.05384	0.43271	0.09221	0.91894	0.15693	-0.40784	0.09221

Note: The weight factors were derived from residual errors of volume and biomass models fitted independently by OLS, which are $1/D^{1.97}$ and $1/D^{2.12}$, respectively, for one- and two-variable volume equations, and $1/D^{2.28}$, $1/D^{2.12}$ and $1/D^{2.05}$ for one-, two- and three-variable aboveground biomass equations. This also applies to Table 3.

Table 3 Fit statistics of compatible tree volume and aboveground biomass equations

Models	R^2		SEE		MPE(%)	
	Volume	Biomass	Volume	Biomass	Volume	Biomass
One-variable	0.9543	0.9559	89.80	49.25	4.81	4.71
Two-variable	0.9844	0.9654	52.59	43.79	2.82	4.19
Three-variable	0.9845	0.9670	52.53	43.88	2.82	4.10

Note: R^2=Determination coefficient, SEE=Standard error of estimate, MPE=Mean prediction error.

Test results for comparison between models

The compatible one, two and three-variable aboveground biomass equations were used to calculate the statistics of t, F_A and F_B from expressions (10)–(12), and they were compared with the critical values for a=0.05 to determine whether the differences were statistically significant (Table 4).

Table 4. Statistics of comparison among compatible aboveground biomass equations

Comparison among following equations	Statistics		
	t	F_A	F_B
One and two-variable equations	2.27*	8.39*	40.18*
One and three-variable equations	2.33*	9.07*	24.62*
Two and three-variable equations	0.81	1.06	7.32*

Note: "*" means significant difference.

Discussion

As shown in Table 3, for the one variable model, the R^2 and MPE values of tree volume and aboveground biomass equations were

not very different, and the R^2 values were both >0.95 while the *MPE* values were both <5%. For two-variable models, the statistical indices of volume equations improved, as shown by reductions in *SEE*-value by about 41% and *MPE*-values by about 2%. The statistical indices of aboveground biomass equations improved slightly, as shown by reductions in *SEE*-value of about 11% and in *MPE*-values by only 0.5%. A tree trunk can be described approximately as a cylinder for which volume can be reasonably accurately computed using diameter and height. However, the aboveground biomass is composed of two major components, stem and crown, which have complementary effects on biomass estimates: for trees of equal diameters, stem biomass increases with height and crown biomass decreases, and vice versa. Thus, the aboveground biomass mainly depends upon the trunk diameter, which is consistent with the conclusion presented by West et al. (1997 and 1999). For the compatible equations system for estimating aboveground biomass and components, when biomass models were expanded from one variable to two and three variables, the regression of stem biomass equations improved significantly, but the regressions of aboveground biomass and other components equations improved slightly (Zeng and Tang 2010). Our research achievement confirmed that this analysis is reasonable.

The results in Table 4 show that estimates from both two-variable and three-variable biomass models are significantly different from those of the one-variable biomass model. This means the addition of tree height and crown width improves the precision of predictions of aboveground biomass models. Comparison of two-variable with three-variable models demonstrated that the statistics t and F_A showed no significant difference, while F_B showed significant difference. These results mean that the contribution of crown width to aboveground biomass estimation was statistically significant. The two statistics t and F_A mainly considered the predicted estimates while F_B mainly considered whether the sum of squared errors decreased significantly with inclusion of another explainable variable. In summary, the prediction precision of one-variable biomass model is more than 95%, so the one variable model can be applied to estimate forest biomass over large-scale regions. The prediction precision of the two-variable biomass model was only 0.5% higher than that of the one-variable model, but the difference was statistically significant. The prediction precision of the three-variable biomass model was almost the same as that of the two-variable model.

Finally, we analyzed the properties of biomass conversion factor ($CF=M/V$) with increasing diameter and height. The change trends of this biomass conversion factor for Masson pine in south China based on diameter and height are shown in Figs. 1 and 2. The conversion factor decreased dependently with increasing diameter or height, and the relationship to height was closer (if power functions were fitted to the *CF-D* and *CF-H* data sets, the determination coefficients were 0.0985 and 0.2491, respectively). The effect of the dependent relationship between D and H cannot be ignored. As shown in Table 2, the parameter c_1 in the conversion function on one variable was negative, consistent with the trend in Fig. 1. Two parameters in the conversion function on two variables were offset to some extent, and c_1 was positive while c_2 was negative. This was because, at equal tree volumes, the crown biomass of a thin and tall tree in dense forest is less than that of a thick and short tree in sparse forest or that of an isolated tree, and the conversion factor is smaller. At equal tree heights, the crown biomass of a large tree is more than that of a small tree, and the conversion factor is larger.

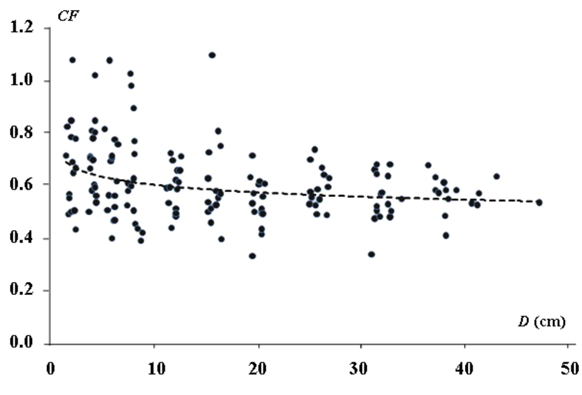

Fig. 1 Conversion factor changes with diameter

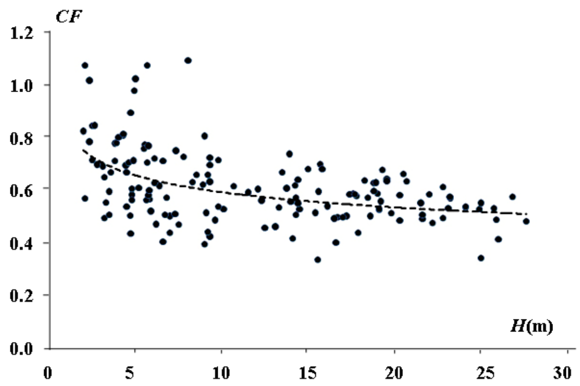

Fig. 2 Conversion factor changes with height

Conclusions

Based on the tree volume and aboveground biomass data of Masson pine in south China, we developed one-, two- and three-variable aboveground biomass equations and conversion functions compatible with tree volume by using error-in-variable simultaneous equations. The tree volume and aboveground biomass equations were fitted simultaneously as a whole. Consequently, the equations were highly harmonious and the parameter estimates were relatively stable. The aboveground biomass and tree volume equations can be used independently for estimation of forest biomass and forest volume. If previous volume equations are still applied in forest resource monitoring, the conversion functions should be used to convert tree volume to aboveground biomass, and the estimates of forest biomass and forest volume will be coordinated. We conclude as followings:

(1) The incongruity between volume and biomass estimates can be effectively resolved using error-in-variable simultaneous

equations. Tree volume and aboveground biomass equations and the conversion function can be established simultaneously, so that the three models are compatible with each other.

(2) The comparison results between one-, two- and three-variable models show that when tree height and crown width are used as other explainable variables together with diameter, the regression of volume equation will be substantially improved, while the regression of aboveground biomass equations will be slightly improved.

(3) For the one-variable biomass conversion function, the conversion factor decreases with increasing tree diameter. For the two-variable biomass conversion function, the conversion factor increases with increasing diameter but decreases with increasing tree height.

(4) From the one-variable compatible equations established for Masson pine, the prediction precision of tree volume and aboveground biomass estimates was more than 95%. From the two-variable compatible equations, the precision of tree volume estimates was >97% but the precision of aboveground biomass estimate was only 0.5% higher than that from the one-variable equation.

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